Jurnal
Teknologi

Full paper

EEG Signal of Epiliptic Patient by Fast Fourier and Wavelet Transforms

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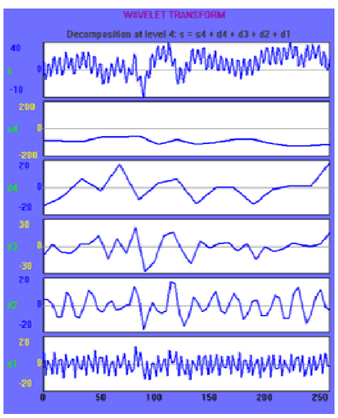
Article history

Received :24 April 2012
Received in revised form :24 December 2012
Accepted: 12 February 2013

Graphical abstract



Abstract

Electroencephalography (EEG) is one of the field in diagnosing epilepsy. Analysis of the EEG records can provide valuable insight and improve understanding of the mechanisms causing epileptic disorders. In this paper, the fast Fourier transform (FFT) and wavelet transform are used as spectral analysis tools of the EEG signals. These methods are chosen because they provide time-frequency shifted on the EEG signals. Since the frequency characteristics are important information that can be observed from the signals, FFT and wavelet transform are among the best methods in analysis of EEG signals. The comparisons between these two methods are also carried out. Result showed that the wavelet transform is better than FFT in analysis of EEG signals. A software for analysing EEG signal is also developed using C++ programming. The software is able to compute and show the results of the analysis signal data by both of the two methods in graphical form.

Keywords: Electroencephalography (EEG); Fast Fourier Transform (FFT); Wavelet Transform (WT)

Abstrak

Electroencephalography (EEG) merupakan salah satu bidang dalam diagnosis epilepsi. Analisis data EEG boleh memberi kita penjelasan yang bernilai dan meningkatkan pemahaman terhadap mekanisme yang menyebabkan penyakit epilepsi. Dalam kajian ini, Penjelmaan Fourier (FFT) dan penjelmaan gelombang kecil (WT) telah digunakan sebagai penganalisis spektrum EEG signal. Dua kaedah ini dipilih kerana kedua-dua kaedah ini mampu menukarkan domain masa bagi isyarat data EEG dengan domain frekuensi. Sifat frekuensi adalah maklumat penting yang boleh diperolehi daripada isyarat EEG. Kelebihan ini menyebabkan Penjelmaan Fourier dan penjelmaan gelombang kecil merupakan antara kaedah terbaik dalam menganalisis isyarat data EEG. Dalam kajian ini, perbandingan terhadap kedua-dua kaedah ini juga dikaji. Keputusan menunjukkan kaedah penjelmaan gelombang kecil adalah lebih baik berbanding dengan kaedah penjelmaan Fourier dalam analisis isyarat data EEG. Selain itu, satu perisian komputer bagi analisis isyarat data EEG juga dicipta dengan menggunakan bahasa C++. Perisian komputer yang dibina dapat menganalisis isyarat EEG dengan kedua-dua kaedah dan keputusan akan ditunjukkan dalam bentuk grafik.

Kata kunci: Electroencephalography; Penjelmaan Fourier; penjelmaan gelombang kecil

■1.0 INTRODUCTION

Electroencephalogram (EEG) is a visible record of the amplified electrical activity generated by the nerve cells of the brain [1]. By placing electrodes on the scalp and amplifying the electrical activity from the brain, EEG can be recorded and appeared in the written form [2]. This recorded EEG known as brain waves, or also called EEG signals.

EEG signals were obtained from four patients who were having epilepsy, as shown in Figure 1. Then these signals were sampled at 256 discrete data in every second using Nicolet One EEG software. Then a 10-second set of data was taken in our analysis.

In this paper, two spectral analysis methods, i.e. fast Fourier transform and wavelet transform, are used to analyze the EEG signals. The objective of the study is to analyze the spectral analysis of the EEG signals which are transformed by FFT and wavelet transform. Besides, the comparisons between these methods were also carried out in order to determine the better method in analysis of the EEG signals. A software have been developed using C++ programming in order to visualize the solution of FFT and WT in graphical form so that the analysis becomes easier.

This paper is organized as follows. Some important information about EEG signals are given in section 2. In sections 3 and 4, FFT and wavelet transform and the application of these methods on the EEG signals were discussed. It is followed by development of software in section 5. Lastly we conclude the work done and give some suggestion for future work.

2.0 EEG SIGNAL

By placing electrodes on the scalp, the signal will be read. Then amplifiers bring the microvolt signals into range where they can be digitalized accurately. Converter changes the signals from analog to digital form and digital computer process the digital data to the written form. Figure 1 shows the EEG signals recorded from an epileptic patient.

In order to analyze the signals, we have to determine the frequency distribution of the signals. Table 1 shows the four major types of frequency of the EEG [3].

Since the frequency characteristic is an important information that can be observed from the signals, FFT and wavelet transform are among the best methods in analysis of EEG signals [4, 5]. These methods provide time-frequency shifted on the EEG signals.

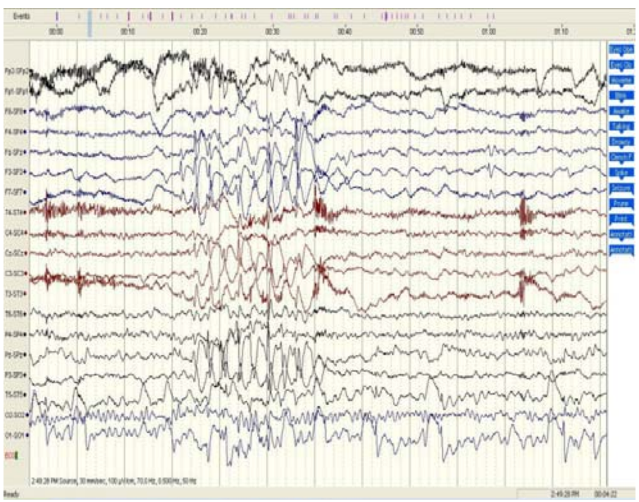


Figure 1 EEG signals recorded from epileptic patients

Table 1 Major types of frequency of the EEG

Delta waves, δ. (<4Hz)	Delta rhythms are slow brain activities, can be seen only in deep sleep stages of normal adults. Otherwise, diagnoses are suggested.
Theta waves, θ. (4-8Hz)	This EEG frequency bands exist in normal infants and children as well as during drowsiness and sleep in adults. Only a small amount of theta rhythms appears in the normal waking adult. Present of high theta activity in awake adults suggests abnormal and pathological conditions.
Alpha waves, α. (8-14Hz)	Alpha rhythms exist in normal adults during relaxed and mentally inactive awakeness. Alpha rhythms are blocked by opening the eyes (visual attention) and other mental efforts such as thinking.
Beta waves, β. (14-30Hz)	Beta activity is mostly marked in front to central region with less amplitude than alpha rhythms. It is enhanced by expectancy states and tension.

3.0 FFT AND THE APPLICATION ON THE EEG SIGNALS

FFT is the fast algorithm to calculate discrete Fourier transform (DFT) [6]. The DFT *X(k)* of a finite duration function x(n) is given as:

$$X(k) = \sum_{n=0}^{N-1} x(n) W_N^{kn} \tag{1}$$

where $W_N = e^{\frac{-j2\pi}{N}}, N = \text{length}[x(n)]\ , k = 0,1,\ldots,N-1.$

Note that, if we are given *N*-point data, the calculation need N^2 step. By FFT, we can reduce this calculation in only $N \, \text{Log}_2 N$ operations. We can illustrate the algorithm of calculating 8-point DFT using FFT as the simplified signal flow graph as shown in Figure 2.

We transform the data by Equation 1. Observe that *X* is a complex vector representing *X(k)* for *k=0,1,2,...,255*. Then we compute the absolute value of *X* to get the magnitude. The magnitude of *X* squared is called the estimated power spectrum. A plot of the estimated power spectrum versus frequency is called a periodogram.

Since the first component of *X* is the sum of the data and has large amplitude, we have to remove it before generating the periodogram. Notice also *X(129),X(130),...,X(255)* are complex conjugates of *X(127),X(126),...,X(1)* respectively. Then the periodogram can be plotted for *X(k), k=1,2,..128*. Figure 3 shows the periodogram for channel Fz at t=1 of patient A, which highest amplitude is occurred at the range of alpha band.

We apply this procedure for all channels at time t=1 until t=10 for all the four patients. The patterns of all periodograms are investigated to identify the abnormality of the signals. From the observations, we found that most of the channel has high amplitude in the range of delta and theta bands. This indicates that the abnormality occurred to the EEG signals of the epileptic patient. Then, the highest amplitude's range for each channel is observed to determine which channels have to be concerned on diagnosing epilepsy.

Table 2 shows the differences of the highest amplitude's range for each channel of patient A. Let take $10^8\ \mu V$ and above as the higher amplitude's value of the abnormality of the periodograms. The classification of normal or abnormal of the channel at that time are summarised in Table 3, which conclude that most of the signal showing abnormal pattern between t=5 to t=8.

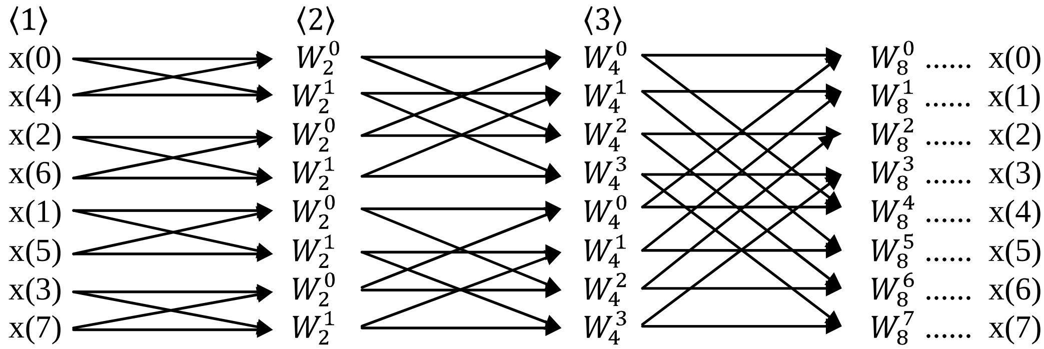


Figure 2 Simplified signal flow graph of 8-point DFT

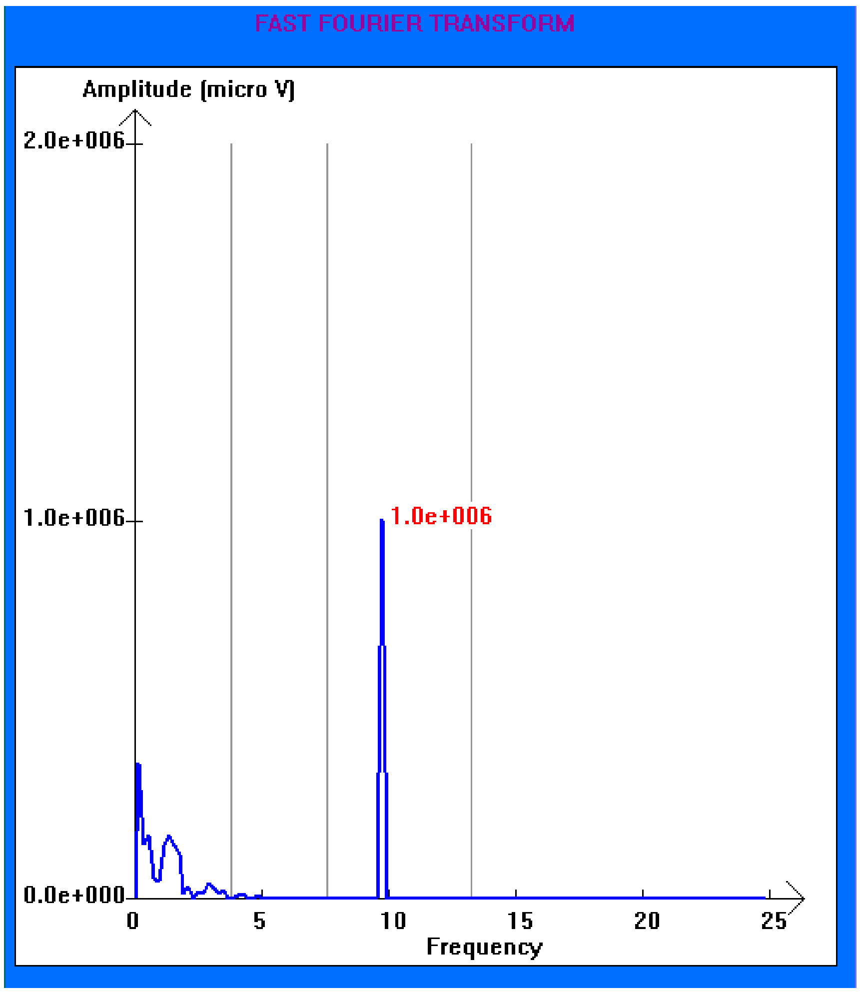


Figure 3 The periodogram for channel Fz at t=1 of patient A

Table 2 The highest amplitude's range for each channel in spectral plot for EEG signal of patient A (μV)

t=	1	2	3	4	5	6	7	8	9	10
Fp1	1.3E+07	1.5E+06	1.9E+06	2.4E+07	6.2E+08	3.3E+08	1.5E+08	9.4E+07	7.3E+07	6.6E+07
Fp2	1.8E+06	3.7E+06	4.8E+06	1.1E+08	5.3E+08	5.3E+08	1.4E+08	1.3E+08	4.1E+07	2.0E+07
F3	2.1E+06	1.4E+06	8.4E+05	1.1E+08	3.8E+07	1.8E+07	2.6E+07	3.6E+07	3.9E+07	4.6E+07
F4	1.7E+07	2.3E+06	2.8E+06	1.0E+07	7.9E+07	4.7E+07	3.3E+07	5.7E+07	5.6E+07	2.2E+07
C3	6.1E+06	4.7E+06	6.0E+06	1.0E+08	1.1E+08	7.4E+07	7.9E+07	4.4E+07	2.3E+07	7.7E+07
C4	5.5E+07	1.5E+06	8.2E+06	8.3E+06	1.9E+08	1.6E+08	1.7E+08	9.7E+07	3.0E+07	3.4E+07
P3	1.2E+07	8.0E+06	6.9E+06	1.3E+08	1.6E+08	2.0E+08	1.5E+08	8.4E+07	8.3E+07	6.6E+07
P4	1.2E+08	4.3E+06	6.9E+07	2.5E+07	4.6E+08	2.9E+08	3.1E+08	1.8E+08	8.2E+07	1.4E+08
O1	2.3E+07	1.0E+07	9.3E+06	3.2E+07	2.5E+08	3.4E+08	3.4E+08	8.0E+07	1.2E+08	2.5E+08
O2	5.5E+07	4.8E+06	4.8E+07	2.2E+07	2.7E+08	4.8E+08	3.8E+08	2.3E+08	6.9E+07	2.1E+08
F7	5.1E+06	2.4E+06	4.2E+06	1.4E+07	2.8E+08	6.2E+08	2.8E+08	1.0E+08	1.3E+08	9.0E+07
F8	5.6E+06	1.7E+06	1.5E+07	8.8E+07	2.5E+08	1.1E+09	8.1E+08	2.0E+08	3.6E+08	1.0E+08
T3	7.3E+06	7.2E+06	4.8E+06	9.6E+06	2.8E+08	1.1E+09	7.8E+08	1.4E+08	5.3E+08	6.7E+07
T4	2.7E+07	5.5E+06	3.4E+07	4.1E+07	3.0E+08	1.4E+09	1.1E+09	1.3E+08	5.4E+08	1.3E+08
T5	2.3E+07	1.3E+07	6.3E+06	4.8E+07	2.0E+08	7.6E+08	6.3E+08	9.1E+07	2.8E+08	8.2E+07
T6	6.1E+07	7.1E+06	7.4E+07	4.3E+07	2.3E+08	1.1E+09	9.4E+08	1.7E+08	3.5E+08	1.2E+08
A1	1.5E+07	2.1E+07	1.1E+07	1.1E+07	3.8E+08	1.3E+09	8.7E+08	1.2E+08	2.5E+08	1.1E+08
A2	2.0E+07	1.1E+07	2.9E+07	5.0E+07	5.6E+08	1.7E+09	1.3E+09	2.0E+08	3.9E+08	1.2E+08
Fz	1.0E+06	7.8E+05	9.7E+05	7.3E+06	4.3E+07	2.8E+07	1.1E+07	1.3E+07	1.2E+07	1.3E+06
Cz	5.0E+06	2.4E+06	4.8E+06	1.3E+07	2.8E+08	2.5E+08	2.9E+08	1.4E+08	2.1E+08	2.3E+07
Pz	4.3E+07	1.3E+07	2.5E+07	2.2E+08	3.1E+08	1.6E+08	1.4E+08	2.9E+08	5.0E+07	3.4E+08

Table 3 Normal and abnormal for each channel for EEG signal of patient A

t=	1	2	3	4	5	6	7	8	9	10
Fp1	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Normal	Normal
Fp2	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal	Normal
F3	Normal	Normal	Normal	Abnormal	Normal	Normal	Normal	Normal	Normal	Normal
F4	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
C3	Normal	Normal	Normal	Abnormal	Abnormal	Normal	Normal	Normal	Normal	Normal
C4	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Normal	Normal
P3	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Normal	Normal	Normal
P4	Abnormal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Normal	Abnormal
O1	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Abnormal	Abnormal
O2	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Normal	Abnormal
F7	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
F8	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
T3	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
T4	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
T5	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Abnormal	Normal
T6	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
A1	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
A2	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
Fz	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
Cz	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
Pz	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal	Abnormal

■4.0 WAVELET TRANSFORM AND THE APPLICATION ON THE EEG SIGNALS

Wavelets can be defined as "small waves" that have limited duration and 0 average values. They are mathematical functions capable of localizing a function or a set of data in both time and frequency [3].

There are many types of wavelet transforms such as Haar wavelet, Mexican Hat wavelet, Gaussian wavelet, Morlet wavelet, and Daubechies wavelet. In this paper, we use Daubechies wavelet to make the analysis of the signals. The advantage of this wavelet system is it can represent the spiky form of the EEG signals properly.

In this Daubechies system, the different orders of the wavelets that are normally used are 2,3,4,5, and 6. This family of wavelets is known for its orthogonality property and efficient filter implementation. Daubechies order 4 wavelet is found to be the most appropriate for analysis of epileptic EEG signals [3]. The lower order wavelets of the family are identified to be too coarse to represent EEG spikes properly. The higher order ones have more oscillations and cannot represent the spiky form of the absence seizure epileptic EEG signals properly.

The general equations for the scaling functions, $\varphi(t)$ and wavelets, $\psi(t)$ can be written as:

$$\varphi_{jk}(t) = 2^{j/2}\varphi_{00}(2^j t - k) \tag{2}$$

$$\psi_{jk}(t) = 2^{j/2}\psi_{00}(2^j t - k) \tag{3}$$

where $j = 0, 1, 2, \ldots$ is the level of the basis functions and $k = 0, 1, 2, \ldots, 2^j - 1$.

The difficulty of this Daubechies order 4 wavelet is there is no explicit function, so we cannot draw it directly. What we are given is *h(k)*, the coefficients in refinement relation which connect $\varphi(t)$ and translates of $\varphi(2t)$. These scaling function coefficients for normalized D4 are as follows:

$$h(0) = \frac{1+\sqrt{3}}{4\sqrt{2}}$$
$$h(1) = \frac{3+\sqrt{3}}{4\sqrt{2}}$$
$$h(2) = \frac{1-\sqrt{3}}{4\sqrt{2}}$$
$$h(3) = \frac{3-\sqrt{3}}{4\sqrt{2}} \tag{4}$$

Then the scaling function of the D4 transform is given

$$\varphi(t) = h(0)\sqrt{2}\varphi(2t) + h(1)\sqrt{2}\varphi(2t-1) + h(2)\sqrt{2}\varphi(2t-2) + h(3)\sqrt{2}\varphi(2t-3) \tag{5}$$

where $\varphi(t)$ is expressed in terms of $\varphi(2t)$ and its translates. The wavelet functions of the D4 transform is given by

$$\psi(t) = g(0)\sqrt{2}\varphi(2t) + g(1)\sqrt{2}\varphi(2t-1) + g(2)\sqrt{2}\varphi(2t-2) + g(3)\sqrt{2}\varphi(2t-3) \tag{6}$$

where $g(0) = h(3)$, $g(1) = -h(2)$, $g(2) = h(1)$, and $g(3) = -h(0)$. These wavelet and scaling functions can be drawn as shown in Figure 4.

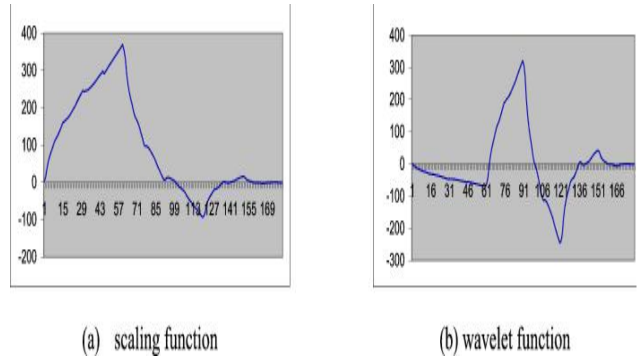


Figure 4 D4 wavelet and scaling functions

By taking the inner product of EEG signals and these basis functions, we can calculate the D4 transform of the signals. The formula for inner product is

$$\langle x(t)|\psi(t)\rangle = trace\left(x(t)^T\psi(t)\right) \tag{7}$$

where *x(t)* are the set of data. The trace of a matrix/vector is the sum of the elements on the main diagonal.

Another approach to construct wavelets is using lifting scheme [7]. The equations of the lifting scheme of D4 transform are:

$$\begin{gathered} d_1 \leftarrow -\sqrt{3}s_1 + d_1 \\ s_1 \leftarrow s_1 + \frac{\sqrt{3}}{4}d_1 + \frac{\sqrt{3}-2}{4}d_{l+1} \\ d_l \leftarrow s_{l-1} + d_1 \\ s_l \leftarrow \sqrt{2+\sqrt{3}s_l} \\ d_l \leftarrow \sqrt{2-\sqrt{3}}\,d_l \end{gathered} \tag{8}$$

The equation involves only multiplication and addition of $\{s_l\}$ and $\{d_l\}$ arrays and computation is found to be faster than conventional operation. The steps that effect changes in value of $\{d_l\}$ are called prediction steps and the one that effect change in value of *{sl}* are called update steps. These operations can be represented in Figure 5.

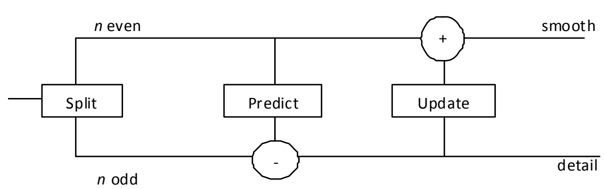


Figure 5 Prediction and updating steps of lifting scheme

The results of the transformations are shown in Figures 6 and 7. The calculation was done by Microsoft Visual C++ 6.0.

In order to identify the abnormality of the signals, we have to observe the amplitude at different level of the frequencies of each decomposed signal. In Figure 6, it can be easily seen that the amplitudes of signal in lower level frequency is greater than the higher level. This condition indicates abnormality in this channel of the EEG signal. While in Figure 7, the amplitudes of the signal in lower level frequency is equal or less than the higher level. This condition indicates the normality in this channel of the EEG signal.

We apply this procedure to the signals from all channels at time t=1 to t=10 and the results of abnormal and normal signal of patient A are given in Table 4.

From Table 4, it can be seen that the abnormality occurs at all channels between t=4 to t=9. The amplitude for the lower level frequency at that time also greater than the higher frequency.

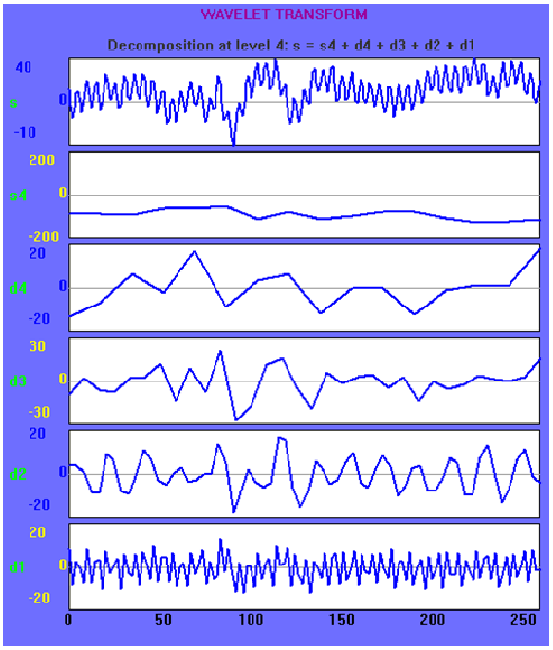


Figure 6 Channel Fz at t=1 of patient A

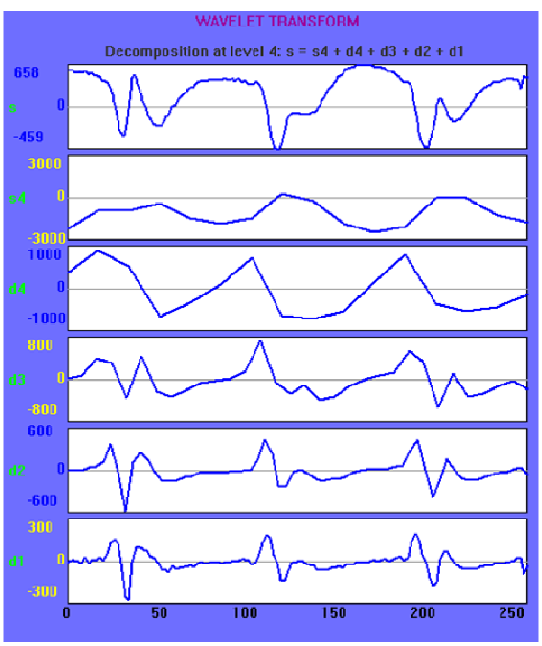


Figure 7 Channel A2 at t=6 of patient A

5.0 FFT VERSUS WT

One of the objectives of this study is to make the comparisons of FFT and wavelet transform in order to determine the better method in analysis of the EEG signals. Time functions are expanded in terms of basic functions in both methods. These functions are exponential for FFT and wavelet for wavelet transform. Other differences of these methods are shown in Table 5.

By this comparison, we can see the differences between FFT and wavelet transform. Time function is expanded in terms of basic functions in both methods. These basis functions are exponential for the FFT and wavelet for wavelet transform. However, the wavelet transform is more efficient than fast Fourier transform. Noticed that there may have some contradiction among these two methods, such as Channel P4 at t=3. The fact is EEG signal are non-stationary, thus there may have some small changes that cannot be realized by FFT and the analysis may change depending on the length of data [4]. So we conclude that for spectral analysis, wavelet transform is more suitable due to the scaling and the shifting properties of the mother wavelet. Besides, wavelet transform can also represent the signals in 3D representation as amplitude, frequency and time. The 3D representation is more convenient for pathological cases, as the epileptic discharges using wavelet transform sub-spectral components can also be represented. These findings concur with the results obtained by Akin [4].

6.0 INTERFACE

A software is developed in this paper by Microsoft Visual C++ 6.0. It can visualize the solution of FFT and WT in graphical form so that the analysis becomes easier. Several colors are used in the programming in order to make the output more attractive and the main point can be highlighted. Figure 8 shows the output of the interface, meanwhile Figure 9 shows a sample result after user clicked option.

Table 4 Normal and abnormal for each channel for EEG signal of patient A

t=	1	2	3	4	5	6	7	8	9	10
Fp1	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
Fp2	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
F3	Normal	Normal	Normal	Abnormal	Normal	Normal	Normal	Normal	Normal	Normal
F4	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Normal	Normal
C3	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
C4	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
P3	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
P4	Abnormal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
O1	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
O2	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
F7	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Normal	Abnormal	Normal
F8	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
T3	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
T4	Normal	Normal	Abnormal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
T5	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
T6	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
A1	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
A2	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal
Fz	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal	Normal
Cz	Normal	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Normal
Pz	Normal	Normal	Normal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal	Abnormal

Table 5 Comparisons of FFT and Wavelet transform

Fast Fourier Transform	Wavelet Transform
The signal is transformed with exponential function	The signal is transformed with wavelet function
The original signal is transformed into a signal complex function and the result is in the frequency domain	The original signal decomposed into another signals in different frequencies.
The time information cannot be seen in the transformed signal.	Both frequency and time information can be obtained from the decomposed signals.

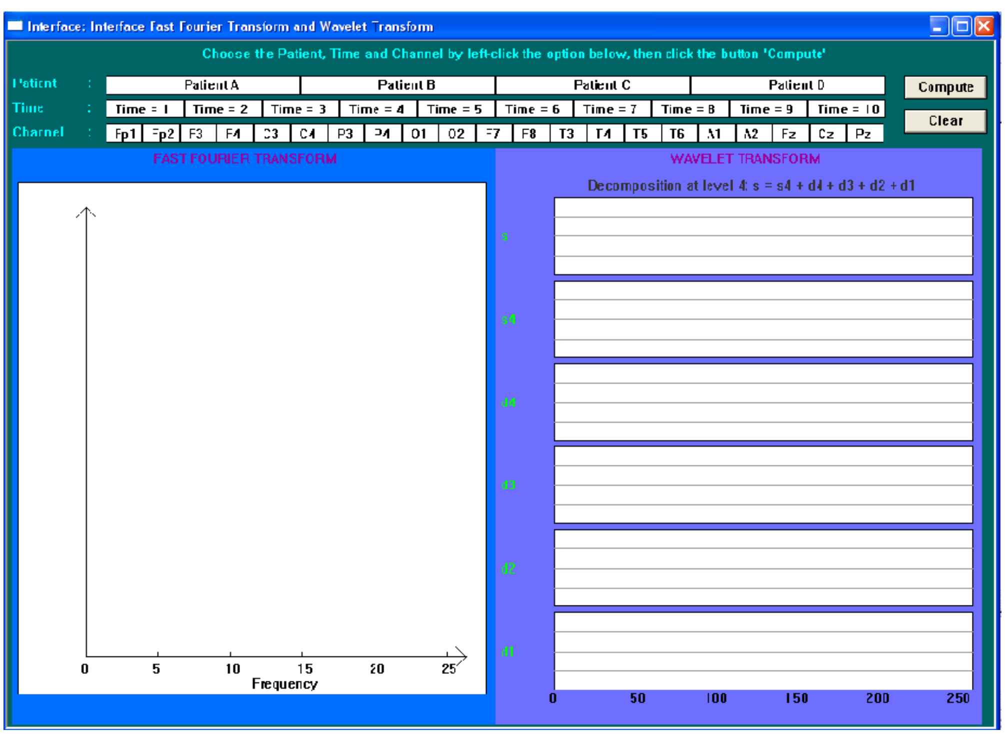


Figure 8 The output of the interface

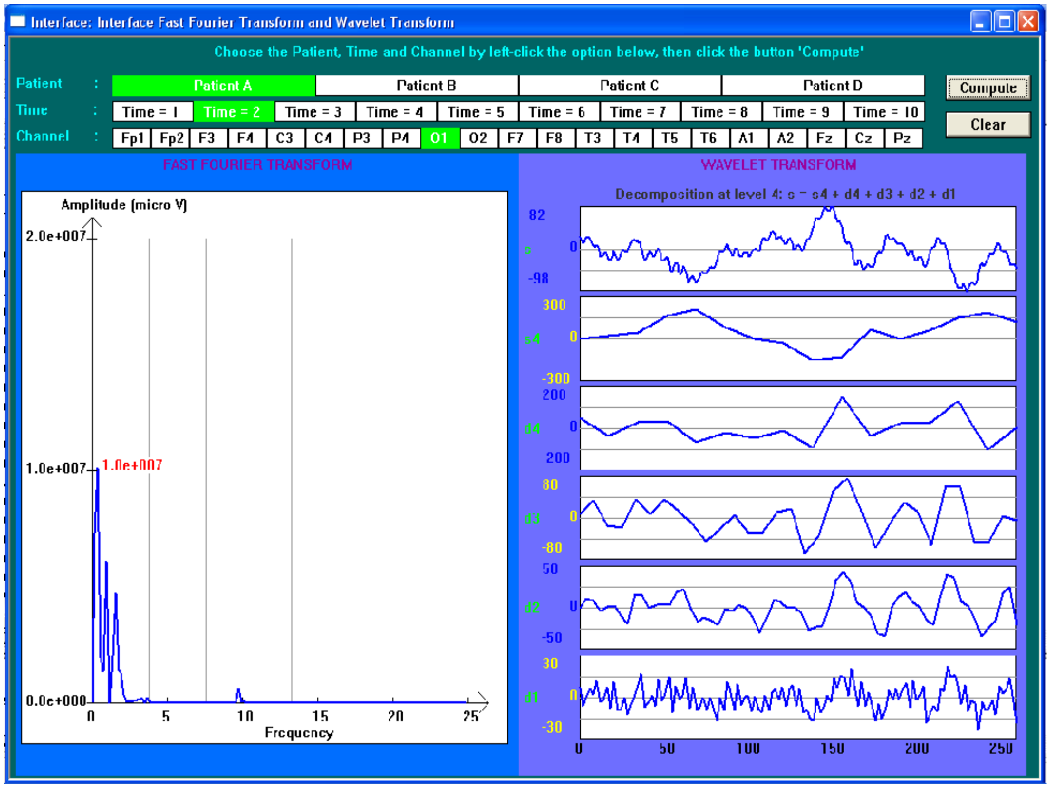


Figure 9 Sample result

In this software, the instruction has been written at the top of software background. As the instruction's guide, user only needs to choose the patient, time and channel by click the left button of mouse. Then click the Compute button, the result will be shown side by side in label boxes. By click the Clear button, the process can be repeated on other option of patients, time or channel without restart the software.

Even the software is designed for calculation of 256 discrete data, but it was designed to be user-friendly. User can also easily modify the input data length into any number that power-of-2 (2^n where n=1, 2, …). User just needs to change the value of row in Interface.h file. To do this, user can replace the data of new patients into the .in extension files. For example file "bt5.in" is representing Patient 2 at time= 5 seconds, whereas file "dt2.in" representing Patient 4 at time = 2 seconds. Besides, the software also makes the results shown in quick understanding form. In FFT, some grey line had been drawn in order to differential the frequency band, also the highest amplitude value is highlighted in red color beside the peak. While WT result also provided some grey line to make the reading of amplitude values become easier.

■7.0 CONCLUSION

The applications of FFT and wavelet transform on the EEG signals are discussed in this paper which conclude that both methods give the same result that is the abnormality of the signals occurred at t=4 until t=6. Therefore, we conclude that the abnormality of the signals happened at that time. Also from the comparison result, we found that WT gave more information due to its 3D output (amplitude, frequency and time). This is ongoing study, we also interest on short-time Fourier transform (STFT) which provides 3D output in future research.

Acknowledgements

The authors would like to thank Ministry of Higher Education for granting the MyBrain15 (MyPhD) scholarship during the study.

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